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Tuci, Elio; Ampatzis, Christos; Vicentini, Federico; Dorigo, Marco

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Evolving homogeneous neuro-controllers for a group of heterogeneous robots: Coordinated motion, cooperation, and acoustic communication

Elio Tuci† (corresponding author) etuci@ulb.ac.be

Christos Ampatzis† campatzi@ulb.ac.be

Federico Vicentini‡ federico.vicentini@polimi.it

Marco Dorigo† mdorigo@ulb.ac.be

† IRIDIA, CoDE, Université Libre de Bruxelles (ULB)

50 Avenue F. Roosevelt, CP 194/6, 1050 Bruxelles, Belgium

Phone: +32 (0)2 6502730

Fax: +32 (0)2 6502715

‡ Robotics Lab, Mechanics Dept., Politecnico di Milano

P.zza Leonardo da Vinci 32, 20133 Milan, Italy

Abstract

This paper illustrates a simulation model in which artificial evolution is used to design homogeneous control structures and adaptive communication protocols for a group of three autonomous simulated robots. The agents are required to cooperate in order to approach a light source avoiding collisions. The robots are morphologically different: two of them are equipped with infrared sensors, one with light sensors. Thus, the two morphologically identical robots should take care of obstacle avoidance; the other one should take care of phototaxis. Since all the agents can emit and perceive sound, the group's coordination of actions is based on acoustic communication. The results of this study are a "proof-of-concept": they show that dynamic artificial neural networks can be successfully synthesised by artificial evolution to design the neural mechanisms required to underpin the behavioural strategies and adaptive communication capabilities demanded by this task. Post-evaluation analyses unveil operational aspects of the best evolved behaviour. Our results suggest that the building blocks and the evolutionary machinery detailed in the paper should be considered in future research works dealing with the design of homogeneous controllers for groups of heterogeneous cooperating and communicating robots.

Key Words: Collective robotics, evolutionary robotics, dynamic neural networks, social behaviour, coordinated motion, signalling.

1 Introduction and motivation

This paper illustrates a set of simulations in which Evolutionary Robotics methods are used to automatically design, through artificial evolution, adaptive communication mechanisms for a swarm of autonomous robots.

Communication is particularly important in any type of multi-robot system because it allows the coordination of actions in scenarios that require cooperation among the agents. Several types of communication protocols have been employed by roboticists to improve the effectiveness of the collective behaviour of a group of robots. Among them, situated communication protocols are becoming increasingly popular owing to their relevance in the domain of swarm robotics. The latter indicates a research field dedicated to the study of how relatively simple physically embodied agents can be designed such that a desired collective behaviour emerges from the local interactions among agents and between the agents and the environment [see 8, 9]. Situated communication refers to social interactions in which the physical instantiation of the message contributes to define its semantics [see 6, for more details]. In other words, the semantics of a signal is grounded in the perceptual experience of the receiver.[1] A classic example of situated communication in nature is stigmergy in social insects [see 12, 15]. Stigmergy is a method of communication where individuals communicate with each other by modifying their local environment. Ants, by laying down pheromone along their trail, mutually influence each others behaviour.

Swarm robotics represents a novel way of doing collective robotics in which autonomous cooperating agents are controlled by distributed, and local rules. That is, each agent uses individual mechanisms and local perception to decide what action to take. In a multi-robot system with these characteristics, (situated) communication refers to those circumstances in which the individual actions carried out by an agent, by perturbing the perceptual state of one or more observers, make possible various forms of social coordination among the members of the group [see 4]. Swarm robotics systems are of particular interest for roboticists since (i) the failure of individual components does not significantly hinder the performance of the group (i.e., robustness); (ii) cooperative behaviour makes it possible to reduce the complexity of the individuals (i.e., simplicity of single units), and (iii) the control mechanisms used are not dependent on the number of agents in the swarm (i.e., scalability).

On going research work in swarm robotics is focusing on the development of design methods to obtain effective group level behaviours from the definition of individual mechanisms and to ground the semantics of communication into the perceptual experience of single agents [see 17, 26, 28]. The research work presented in this paper aims to contribute to the development of swarm robotics systems through the

[1] An alternative to situated communication are abstract communication protocols, in which the physical signal (the medium) that transports the message does not have any semantic properties. Only the content of the message has meaning. Examples of abstract communication are protocols in which messages are exchanged by robots through wireless Ethernet [see 25].

study of a particular scenario that requires a swarm of robots to use communication in order to perform a collective navigation task. In particular, our objective is to prove that evolutionary robotics methods can be successfully applied to the design of homogeneous controllers for a morphologically different swarm of robots.

Evolutionary robotics is a methodological tool to automate the design of robots' controllers [see 21]. Evolutionary robotics is based on the use of artificial evolution to find sets of parameters for artificial neural networks that guide the robots to the accomplishment of their objectives, avoiding dangers. As far as it concerns the subject of this study, the evolutionary robotics methods allow us to develop adaptive communication mechanisms that are grounded on the perceptual experience of the receiver and fully integrated with all the other underlying structures that underpin the behavioural repertoire of each robot. This is because, with respect to other design methods, evolutionary robotics doesn't require the designer to make strong assumptions concerning what behavioural and communication mechanisms are needed by the robots. The experimenter defines the characteristics of a social context in which robots are required to cooperate. The agent's mechanisms for communicative and non-communicative behaviour are determined by an evolutionary process which favours (through selection) those solutions which improve the "fitness" (i.e., a measure of an agent's or group's ability to accomplish its task) of an agent and/or of a group of agents.

In evolutionary robotics, the homogeneous approach (i.e., robots of a group that share the same controller cloned in each agent) is extensively used to deal with morphologically identical robots. This approach is preferred to alternative solutions because it facilitates the design process. For example, the evaluation of the collective behaviour of different homogeneous groups can be directly used to quantitatively estimate the effectiveness of their control structures and subsequently to compare them. If the robots of a group do not share the same controller, it becomes less intuitive to define the criteria to estimate, from the observation of the collective behaviour, the effectiveness of each control structure within a group and to compare different controllers associated with different groups [see 22]. Moreover, the homogeneity of control structures does not preclude the emergence of behavioural specialisations. For example, the work of Quinn et al. [24] shows that leader/follower specialisation can be obtained in a homogeneous group of robots by using dynamical neural network controllers. However, to the best of our knowledge, the homogeneous approach has never been employed in the context of morphologically different robots. In this latter context, neural plasticity may be required to deal with: (a) specialisation or "role assignment" among morphologically similar robots, as well as (b) to account for the morphological differences which characterise the sensory-motor apparatus of the agents. In this paper, the process by which a single controller adapts to morphologically different robots is referred to as "dynamic speciation". Given the nature of the adaptive task described in this paper, we decided to use it as a test-bed to explore the potentiality of the homogeneous approach to design controllers for morphologically different robots.

The results of this study are a "proof-of-concept": they show that dynamic artificial neural networks can be successfully synthesised by artificial evolution to design the neural mechanisms required to underpin the behavioural strategies and adaptive communication capabilities demanded by the task. In particular, we developed a sound signalling system that allows a group of morphologically heterogeneous agents that differ in their sensory capabilities to coordinate their actions in order to approach a light bulb without collisions. Post-evaluation analyses unveil operational aspects of the best evolved behaviour. For example, we show that adaptive group behaviour can be achieved without the need of (i) individual built-in mechanisms for distinguishing between "self" and "non-self" produced signal, and of (ii) complex neural structures that regulate the turn-taking during communication.

1.1 Structure of the paper

In what follows, we first present a review of previous work in which control mechanisms for communicative and non-communicative behaviour in swarm robotic systems have been designed by using the evolutionary robotics methods (see section 2). In section 3, we describe the simulation scenario investigated in this research work. In sections 4, 5, 6, and 7 we describe methodological issues of our study. In section 8, we illustrate the results and post-evaluation analysis of our simulations. Discussion and conclusions are presented in sections 9 and 10.

2 State-of-the-art

In this section we review research work focused on the issue of designing, through artificial evolution, neural mechanisms for communicative and non-communicative behaviour in swarms of autonomous robots. In particular, we describe those works, in which, like in ours, the structure of the communication (i.e., syntax and semantics) are automatically designed by the evolutionary process. Consequently, we do not consider those interesting works on communication in multi-robot systems, in which the mechanisms for social interactions are designed by using other methods than ER. For a survey of work in those fields, we refer the reader to the following articles [2, 5, 11, 25].

There are a number of works carried out in the recent past in which agents asked to solve rather simple tasks that require cooperation and coordination develop simple forms of ritualised social interactions and/or signalling capabilities. In the work described in [23, 24], a team of robots is required to move in an arbitrarily chosen direction by remaining at a distance from each other smaller than the range of their infrared sensors. This work is particularly important because it shows that it is possible to design, through artificial evolution, neural mechanisms which, by simply using the infrared sensors readings, allow a group of homogeneous robots to engage themselves in social interactions which result in the emergence of roles such as leader/follower. The authors also describe the evolution of communication among the robots by showing that behaviour for social coordination first evolves in a non-communicative context, and only subsequently acquires its adaptive function. Still in the domain of social interactions for collective navigation tasks, Baldassarre et al. [3] evolved neuro-controllers for a group of homogeneous robots required to move together towards a target. Contrary to the work described in [24], Baldassarre et al. made use of a dedicated communication channel in the form of a loudspeaker continuously emitting a tone and directional microphones.

In the work described in [18, 19], the authors illustrate the evolution of communicative behaviour based on a simple vocabulary consisting of 4 signals. This communication protocol is used by a group of four robots to halt in two target areas so that at any time each target area doesn't host more than half of the team. In [7], the author describes an experiment in which two autonomous agents, equipped with sound sensors and effectors, have to remain close to each other as long as possible. An operational description of the best evolved solutions reveals that the sound signalling system is used by the agents both for self-stimulation and for social interaction. This evidence seems to go against a shared perspective in biology/psychology which tends to distinguish the behaviour of natural organisms in socially and non-socially relevant. The author uses the counter-intuitive result of his analysis to point out the importance of grounding the functional description of the behaviour of natural organisms into "what we know about the operation (at different level) of the system concerned" [7, p. 43].

The work of Trianni and Dorigo [26] points to the advantages of evolved versus hand-coded acoustic communication protocols in a task in which a group of physically linked robots is required to move while avoiding holes in the ground. The work shows that the behaviour of swarms exploiting an evolved acoustic communication protocols is more robust than the behaviour of swarms using a hand-designed protocols. Similarly, Ampatzis et al. [1] show that a categorization task can be more efficiently performed by a group of two robots when the social interactions are mediated by a simple evolved acoustic communication protocol.

Our experiment is strongly based on some of the research works described in this section. For example, we draw inspiration from [7] for modelling the sound signalling system of our robots (see section 5). Furthermore, we draw inspiration from [24], in order to design the fitness function described in section 4. Other aspects of our work such as the nature of the cooperative scenario used to investigate issues concerning the evolution of acoustic communication (i.e., social interactions in morphologically heterogeneous robots) and other methodological choices are original and innovative. In section 9, we point the reader to similarities and differences between our work and those described in this section, and we highlight the novel and interesting parts of our research work.

3 Experimental setup

[Insert here Figure 1]

We consider the following experiment: three simulated robots—referred to as robots or agents hereafter—are required to navigate towards a light source, while remaining close to each other. The robots are placed in an arena, as shown in Figure 11. The arena is composed of walls and a light that is always turned on. The light can be situated at the bottom left corridor (*Env. L*) or at the bottom right corridor (*Env. R*). The robots are initialised with their centre anywhere on an imaginary circle of radius 12 cm centred in the middle of the top corridor, at a minimum distance of 3 cm from each other. The initial orientation of each robot is determined by applying an angular displacement randomly chosen in the interval $[-30°, 30°]$ with respect to a vector originating from the centre of the robot and pointing towards the centroid of the group. The goal of the robots is (i) to navigate towards the light whose position changes according to the type of environment they are situated in, (ii) to avoid collisions.

The peculiarity of the task lies in the fact that the robots are equipped with different sets of sensors. In particular, two robots are equipped with infrared and sound sensors but they have no ambient light sensors. These robots are referred to as R_{IR} (see Figure 11a). The other robot is equipped with ambient light and sound sensors but it has no infrared sensors. We refer to this robot as R_{AL} (see Figure 11b). Robots R_{IR} can perceive the walls and other agents through infrared sensors, while the robot R_{AL} can perceive the light. Therefore, given the nature of the task, the robots are forced to cooperate in order to accomplish their goal. In fact, it would be very hard for each of them to solve the task solely based on their own perception of the world. R_{AL} can hardly avoid collisions; R_{IR} can hardly find the light source. Thus, the task requires cooperation and coordination of actions between the different types of robots.

Although the robots differ with respect to their sensory capabilities, they are homogeneous with respect to their controllers. That is, the same controller, synthesised by artificial evolution, is cloned in each member of the group. Both types of robots are equipped with a sound signalling system (more details in section 5). However, contrary to other studies [see 18, 19, 3], we do not assume that the agents are capable of distinguishing their own sound from that of the other agents. The sound broadcast into the environment is perceived by the agent through omnidirectional microphones. Therefore, acoustic signalling is subject to problems such as the distinction between own sound from those of others and the mutual interference due to lack of turn-taking [see 7].

Notice that the reason why we chose the group to be composed of two R_{IR} and one R_{AL} robot is that this intuitively seems to be the smallest group capable of spatially arranging itself adaptively in order to successfully navigate the considered world. Preliminary studies have shown that with two robot groups, evolution tends to favour solutions in which, during navigation, R_{IR} remains in front of R_{AL}. This type of group has troubles in making the left and the right turn. As we will show in the next sections of this document, a three robot group in which R_{AL} tends to remain behind the two R_{IR} fellows, employs safer and more robust navigation strategies, that allow the robots to successfully make both turns.

4 The fitness function

During evolution, each genotype is translated into a robot controller, and cloned onto each agent. Then, the group is evaluated twelve times, six trials in *Env. L*, and six trials in *Env. R*. The sequence order of environments within the twelve trials has no bearing on the overall performance of the group since each robot controller is reset at the beginning of each trial. Each trial (e) differs from the others in the initialisation of the random number generator, which influences the robots' starting position and orientation, and the noise added to motors and sensors. Within a trial, the robot life-span is 400 simulated seconds (4000 simulation cycles). In each trial, the group is rewarded by an evaluation function f_e which seeks to assess the ability of the team to approach the light bulb, while avoiding collisions and staying within the range of the robots' infrared sensors:[2].

$$f_e = KP\Big(\sum_{t=i}^{T}[(d_t - D_{t-1})(\tanh(S_t/\rho))]\Big).$$

As in [24], the simulation time steps are indexed by t and T is the index of the final time step of the trial; d_t is the Euclidean distance between the group location at time step t and its location at time step $t = 0$, and D_{t-1} is the largest value that d_t has attained prior to time step t. Therefore, the term $(d_t - D_{t-1})$ measures any gain that the team has made on its previous best distance from its initial location which is taken to be the centroid of the group.

The factor $\tanh(S_t/\rho)$ reduces any fitness increment given by $(d_t - D_{t-1})$ when one or more robots are outside of the infrared sensor range: S_t is a measure of the team's dispersal beyond the infrared sensor range ρ ($\rho = 24.6$ cm) at time step t. Recall that robot R_{AL} has no infrared sensors. Therefore, it does not have a direct feedback at each time-step of its distance from its group-mates. Nevertheless, the sound can be indirectly used by this robot to adjust its position within the group. If each robot is within ρ range of at least another, then $S_t = 0$. Otherwise, the two shortest lines that connect all three robots are found and S_t is the distance by which the longest of these exceeds ρ. The function $\tanh(x)$ assures that, as the robots begin to disperse, the team's score increment falls sharply.

$P = 1 - (\sum_{i=1}^{3} c_i/c_{max})$ if $\sum_{i=1}^{3} c_i \leq c_{max}$ reduces the score in proportion to the number of collisions which have occurred during the trial, where c_i is the number of collisions of the robot i and $c_{max} = 4$ is the maximum number of collisions allowed. $P = 0$ if $\sum_{i=1}^{3} c_i > c_{max}$. The team's accumulated score is multiplied by $K = 3.0$ if the group moved towards the light bulb, otherwise $K = 1.0$. Note that a trial is

[2]Note that, this fitness function is very similar to the one used in [24] from which it mainly differs for the parameter K. This parameter has been introduced to give a selective advantage to those groups which move towards the light bulb. In order to facilitate comparisons between our work and that detailed in [24], we provide a description of the fitness function which uses a similar mathematical notation employed in [24]

terminated early if (a) the team reached the light bulb (b) the team distance from the light bulb exceeds an arbitrary limit set to 150 cm, or (c) the team exceeds the maximum number of allowed collisions c_{max}.

5 The robots

[Insert here Figure 2]

The controllers are evolved in a two-dimensional simulation environment which models the kinematics of simple geometries and the functional properties of three types of sensors: infrared, ambient light, and sound sensors [see 27, for a detailed description of the simulator]. As illustrated in Figure 11a and 11b, our robots are modelled as circular objects of 5.8 cm of radius. Differential Drive Kinematics equations, as presented in [10], are used to update the position of the robots within the environment.

Each robot R_{IR} has 12 infrared sensors (IR_i) placed on the perimeter of its circular body (see Figure 11a). Robot R_{AL} has two ambient light sensors (AL_1) and (AL_2) positioned at $\pm 67.5°$ with respect to its facing direction (see Figure 11b). The signal of both infrared sensors and ambient light sensors is a function of the distance between the robot and the obstacle.[3]

[Insert here Figure 3]

Both R_{IR} and R_{AL} robots are equipped with a loud-speaker (L) that is situated in the centre of the body of each robot, and with two omnidirectional microphones (S_1 and S_2), placed at $\pm 45°$ with respect to the robot's heading. Sound is modelled as an instantaneous, additive field of single frequency with time-varying intensity ($\eta_i \in [0.0, 1.0]$) which decreases with the square of the distance from the source, as previously modelled in [7]. Robots can perceive signals emitted by themselves and by other agents. The modelling of the perception of sound is inspired by what described in [7]. There is no attenuation of intensity for self-produced signal. The perception of sound emitted by others is affected by a "shadowing" mechanism which is modelled as a linear attenuation without refraction, proportional to the distance (δ_{sh}) travelled by the signal within the body of the receiver [see 7, for details]. This distance is computed as follows:

$$\delta_{sh} = \delta_{sen}(1 - A), \qquad 0 \leq A < 1, \qquad A = \frac{\delta^2 - R^2}{\delta_{sen}{}^2} \tag{1}$$

where δ_{sen} is the distance between the sound source and the sensor, δ is the distance between the sound source and the centre of the body of the receiver, and R is the robot's radius (see also Figure 11). The "self" component of the sound signal is simply equal to η_i. In order to calculate the "non-self" component, first we scale the intensity of sound emitted by the sender (η_j) by applying the inverse square law with

[3] The morphological structure and sensory apparatus of our robots model some of the characteristics of the *s-bots*. The *s-bots* are small wheeled cylindrical robots, 5.8 cm of radius, equipped with a variety of sensors, and whose mobility is ensured by a differential drive system (see [20] for details).

respect to the distance between the sound source and the microphones of the receiver. Subsequently, we multiply the scaled intensity with an attenuation factor ψ which ranges linearly from 1 when $\delta_{sh} = 0$ to 0.1 when $\delta_{sh} = 2R$. To summarise, the reading $\hat{S}_{is}$ of each sound sensor s of robot i is computed as follows:

$$\hat{S}_{is} = \text{self} + \text{non-self}; \qquad \begin{aligned} \text{self} &= \eta_i \\ \text{non-self} &= \sum_{\substack{j\in[1,3]\\ j\neq i}} \eta_j \frac{R^2}{\delta^2_{sen}} \psi \end{aligned} \tag{2}$$

The auditory receptive field of each microphone is bounded within the interval $[0.0, 1.0]$. Therefore, the sound sensor can be saturated by the "self" emitted sound in case a robot emits at its highest intensity ($\eta_i = 1.0$).

10% uniform noise is added to all sensor readings, the motor outputs and the position of the robot.

6 The robots' neural controller

The agent controller is composed of a network of five inter-neurons and an arrangement of six sensory neurons and three output neurons (see Fig. 11c). The sensory neurons receive input from the agent sensory apparatus. Thus, for robots R_{IR}, the network receives the readings from the infrared and sound sensors. For robots R_{AL}, the network receives the readings from the ambient-light and sound sensors. The inter-neuron network (from N_7 to N_{11}) is fully connected. Additionally, each inter-neuron receives one incoming synapse from each sensory neuron. Each output neuron (from N_{12} to N_{14}) receives one incoming synapse from each inter-neuron. There are no direct connections between sensory and output neurons. The network neurons are governed by the following state equation:

$$\frac{dy_i}{dt} = \begin{cases} \frac{1}{\tau_i}(-y_i + gI_i) & i \in [1,6] \\ \frac{1}{\tau_i}\left(-y_i + \sum\limits_{j=h}^{k} \omega_{ji}\sigma(y_j + \beta_j) + gI_i\right) & i \in [7,14];\ \sigma(x) = \frac{1}{1+e^{-x}} \end{cases} \tag{3}$$

where, using terms derived from an analogy with real neurons, y_i represents the cell potential, τ_i the decay constant, g is a gain factor, I_i the intensity of the sensory perturbation on sensory neuron i, ω_{ji} the strength of the synaptic connection from neuron j to neuron i, β_j the bias term, $\sigma(y_j + \beta_j)$ the firing rate. For each i the indexes h and k are set by taking into account the network architecture. The cell potentials y_i of the 12^{th} and 13^{th} neuron, mapped into [0.0,1.0] by a sigmoid function σ and then linearly scaled into $[-6.5, 6.5]$, set the robot motors output. The cell potential y_i of the 14^{th} neuron, mapped into $[0.0, 1.0]$ by a sigmoid function σ, is used by the robot r to control the intensity of the sound emitted η_r. The following parameters are genetically encoded: (i) the strength of synaptic connections ω_{ji}; (ii) the decay constant τ_i of the inter-neurons and of neuron N_{14}; (iii) the bias term β_i of the sensory neurons, of the inter-neurons, and of the neuron N_{14}. The decay constant τ_i of the sensory neurons and of the output neurons N_{12} and N_{13} is set to 0.1. Cell potentials are set to 0 any time the network is initialised or reset, and circuits are integrated using the forward Euler method with an integration step-size of $dt = 0.1$.

7 The evolutionary algorithm

A simple generational genetic algorithm is employed to set the parameters of the networks [see 14]. The population contains 80 genotypes. Generations following the first one are produced by a combination of selection with elitism, recombination and mutation. For each new generation, the three highest scoring individuals ("the elite") from the previous generation are retained unchanged. The remainder of the new population is generated by fitness-proportional selection (also known as roulette wheel selection) from the individuals of the old population. Each genotype is a vector comprising 84 real values (i.e., 70 connection weights, 6 decay constants, 7 bias terms, and a gain factor). Initially, a random population of vectors is generated by initialising each component of each genotype to values chosen uniformly random from the range [0,1]. New genotypes, except "the elite", are produced by applying recombination with a probability of 0.3 and mutation. Mutation entails that a random Gaussian offset is applied to each real-valued vector component encoded in the genotype, with a probability of 0.15. The mean of the Gaussian is 0, and its standard deviation is 0.1. During evolution, all vector component values are constrained to remain within the range [0,1]. Genotype parameters are linearly mapped to produce network parameters with the following ranges: biases $\beta_i \in [-4, -2]$ with $i \in [1, 6]$, biases $\beta_i \in [-5, 5]$ with $i \in [7, 14]$; weights $\omega_{ij} \in [-6, 6]$ with $i \in [1, 6]$ and $j \in [7, 11]$, weights $\omega_{ij} \in [-10, 10]$ with $i \in [7, 11]$ and $j \in [7, 14]$; gain factor $g \in [1, 13]$. Decay constants are firstly linearly mapped into the range $[-1.0, 1.3]$ and then exponentially mapped into $\tau_i \in [10^{-1.0}, 10^{1.3}]$. The lower bound of τ_i corresponds to the integration step-size used to update the controller; the upper bound, arbitrarily chosen, corresponds to about 1/20 of the maximum length of a trial (i.e., 400 s).

8 Results

[Insert here Figure 4]

Ten evolutionary simulations, each using a different random initialisation, were run for between 2500 and 3600 generations of the evolutionary algorithm. In particular, the termination criterion for each run was set to a time equal to 86400 seconds of CPU time. The variation in the number of generations among differently seeded evolutionary runs is related to the performances of the robots in each trial. For example, the evolutionary runs with more generations are those in which trials tended to last shorter than the given time limits (i.e., 400 simulated seconds, see also section 4). Figure 11 shows the fitness of the best group at each generation of ten evolutionary runs. Given the way in which the fitness is computed and the dimensions of the world, scores higher than 200 refer to groups that manage to repeatedly get very close to the light in both types of environment. The graph indicates that several runs produced successful groups. However, the graph also indicates that the fitness of the best groups of the most successful evolutionary runs oscillates quite a lot throughout the evolution. These oscillations may be related to the phenomenon of the overestimation of the fitness of the best groups. It may have happened that, during evolution, the best groups took advantages of favourable conditions, which are determined by the existence of between-generation variation in the starting positions and relative orientation of the robots and other simulation parameters. Thus, in the next section, we show the results of a first series of post-evaluation tests aimed to estimate the effectiveness of the best evolved navigation strategies of each run, under circumstances in which the effect of favorable conditions linked to the initialisation of the robots are ruled out.

8.1 First post-evaluation tests

In order to have a better estimate of the behavioural capabilities of the evolved controllers, we post-evaluated, for each evolutionary simulation, the genotype with the highest fitness. The groups of robots controlled by neural networks built from these genotypes are referred to as n. 1 to n. 10, respectively.

[Insert here Figure 5]

During post-evaluation, each group is subject to a set of 1200 trials in both environments. The number of post-evaluation trials per type of environment (i.e., 1200) is given by systematically varying the initial positions of the three robots according to the following criteria: (i) we defined four different types of spatial arrangements in which the robots are placed at the vertices of an imaginary equilateral triangle inscribed in a circle of radius 12 cm and centred in the middle of the top corridor (see Figure 11); (ii) for each spatial arrangement, we identified three possible relative positions of the robot R_{AL} with respect to the walls of the corridor (see white circle in Figure 11); (iii) for each of these (four times three) initial positions, the post-evaluation is repeated one hundred times. The initial orientation of each robot is determined by applying an angular displacement randomly chosen in the interval $[-30°, 30°]$ with respect to a vector originating from the centre of the robot and pointing towards the centroid of the group. The four times three different arrangements take into account a set of relative positions among the robots and between the robots and the walls so that the success rate of the group is not biased by these elements.

For the sake of clarity, we decided to estimate the effectiveness of the robots' behavioural capabilities during post-evaluation by employing a binary criterion (successful/unsuccessful) instead of the fitness function as during evolution. In particular, a group is considered successful if its centroid is less than 10 cm away from the light bulb. However, preliminary tests showed that the "10 cm away from the light bulb" criterion in 400 s trials was too demanding for the robots. Many of the initial positions resulting from the systematic variation as explained above require the robots to spend a lot of the time at their disposal in re-arranging themselves to be able to safely progress towards the light, leaving little time for navigation. It appeared that some of the evolutionary conditions (e.g., the random initialisation of the robots' initial position and the few evaluation trials) did not favour groups capable of quickly arranging themselves for phototaxis regardless their initial positions. Consequently, even groups capable of moving towards the light without colliding resulted very often unsuccessful due to lack of time to fulfil the "10 cm away from the light bulb" criterion. Since our interest in this paper is on collision free navigation strategies and not on other characteristics of the phototactic movement such as the speed (i.e., how quickly the robots get to the light bulb), we decided to make the post-evaluation trials 2.5 times longer than the trials during evolution (i.e., 1000 s, 10000 simulation cycles). This should (i) give the robots enough time to compensate for possible disruptive effects induced by initial positions never or very rarely experienced during evolution[4], and (ii) provide us with a fair estimation of the navigation capabilities of each of the groups selected for post-evaluation. At the beginning of each post-evaluation trial, the controllers are reset (see section 6 for details).

[Insert here Figure 6]

The results of the post-evaluation phase are shown in Figure 11. We notice that the best groups are n. 9 and n. 10, that achieve a performance over 90% in both environments. Groups n. 4 and n. 7 display a performance over 80% in both environments. The performance of all the other groups is clearly unsatisfactory. Groups n. 2, 3, 5, and 8 proved to be capable of accomplishing the task only when located in an *Env. R*, while group n. 1 is particularly effective in *Env. L*. This phenomenon can be explained by considering that the two environments require two different types of turn—a left turn in *Env. L*, and a right turn in *Env. R*. By looking at the behaviour of the groups through a simple graphical interface, we observed that the successful groups employ two different navigation strategies to make the two types of turn (see section 8.2). We also observed that those groups that systematically fail in any of the two environments, lack the capability to make both turns. Note that when looking at the performances of the best evolved groups, as shown in Figure 11, one has to take into account the arbitrary criteria we chose to determine whether or not a group of robots is successful in any given trial: no robot has to collide with the walls or with the other robots. This is a very strict condition, which, given the nature of the task, demands each agent to be very accurate in coordinating its movement. Further post-evaluation

[4] The set of starting conditions during post-evaluation is a subset of the set of starting conditions experienced by the robots during evolution (see section 3 for details). However, while during evolution each group is evaluated on 12 randomly chosen starting conditions, during post-evaluation the best evolved groups are evaluated on a larger set of starting conditions—i.e., 1200.

tests proved that, if we allow the group to make a certain number of collisions (i.e., four collisions) before defining a trial as a failure, then several groups would result almost always successful in both types of environment (data not shown). Whether or not the robots should be allowed to collide or the extent to which a single collision invalidates the performance of the group are issues that go beyond the scope of this paper and shall not be discussed any further.

[Insert here Table 1]

Instead, we focus on other performance measures which tell us more about the characteristics of the best evolved groups. For instance, by looking at the data shown in Table 11, we notice that, except for group n. 2, the majority of the failures in *Env. L*, are due to collisions. In *Env. R*, the performances of all the groups, are sensibly better than those in *Env. L* (see columns 4 and 5, Table 11). If we look at the average distances to the light (see columns 6 and 7, Table 11) and the relative standard deviations (see columns 8 and 9, Table 11), we can see that in *Env. L* failures happen rather far away from the light. For example, for groups n. 3, 5, and 8—100% unsuccessful in *Env. L*—the final distance to the light is almost equal to the initial distance. This denotes a lack of coordination of movement during the initial phase, when the robots have to assume a configuration which favours the group phototaxis. In *Env. R*, the smaller final distances to the light seem to denote a problem, possibly common to several groups, in making the right turn.

In the rest of this section, we concentrate on the analysis of the group n. 9, which proved to be the most effective in the first post-evaluation test. The tests we are going to illustrate have been carried out for all the best evolved groups. It turned out that, successful navigation strategies of any best evolved group are very similar from a behavioural point of view, and in terms of the communication mechanisms exploited to obtain the coordination of actions. Therefore, the reader should consider the operational description of the behaviour of group n. 9 representative of all the successful navigation strategies of any best evolved group. These groups seems to differ in terms of the robustness of the mechanisms that underpin their behaviour rather than on the nature of these mechanisms.

8.2 Group n. 9: A description of the behavioural strategies

In this section we provide a qualitative description of the individual motion of robots group n. 9 as observed through a simple graphical interface.

[Insert here Figure 7]

First of all, we noticed that the systematic variation of the initial positions of the robots during post-evaluation brings about contingencies in which the coordination of movements of the group toward the target requires an initial effort of the robots in re-arranging their relative positions.[5] During this initial phase of a trial a dynamic process guided by the nature of the flow of sensations induces the specialisation of the controllers with respect to the physical characteristics of the robots, and to the relative role that they play in the group. This phase is followed by the navigation phase in which the group maintains a rather regular spatial configuration; that is, the two robots R_{IR} place themselves in between the target and the robot R_{AL}. However, note that while *Env. L* requires the group to make a left turn, *Env. R* requires the group to make a right turn. This asymmetry in the environmental structures corresponds to differences in behavioural strategies employed by the group to reach the target as shown in Figure 11. While in *Env. L* the robots simply turn towards the light keeping their relative positions in the group, in *Env. R* we firstly observe an alignment of the agents along the far right wall (see Figure 11b). Subsequently, the agent close to the corner (see the dark gray line) overcomes the other two and the group starts moving towards the target once the classical configuration of the two robots R_{IR} in between the target and the robot R_{AL} is re-established.

Another important qualitative element is that each of the members of the group is characterised by a movement with a strong angular component (anti-clockwise). In other words, the robots proceed toward the light by rotating on the spot. Within a trial, pure linear movement replaces the rotational behaviour only sporadically and for a very short interval (see movies available at `http://iridia.ulb.ac.be/supp/IridiaSupp2006-006/`). This can happen to avoid an imminent danger of collision or if required by the navigational strategy of the group. The evolution of the rotational movement is not particularly surprising if we think about its effect on the perception of sound. In particular, the rotational movement may introduce rhythm in perception. The oscillations of perceived sound, produced by the rotational movement and/or by the oscillations manifested in signalling behaviour, may provide the robots the cues to adjust their positions relative to each other. Further and deeper investigations on the nature of sound signals and its relationship with the robots' motion will be carried out in the next sections.

The effect of the starting position and the rotational movement are phenomena that have a strong effect on the time it takes to the group to reach the target. Indeed, as resulted from the post-evaluation test, most of the successful trials of group n. 9 last longer than the 400 s given to the groups to complete the task during the evolutionary phase (data not shown).

8.3 Group n. 9: A description of the signalling behaviour

Each robot of the group is required to coordinate its actions in order (i) to remain close to the other two agents without incurring into collisions, and (ii) to make actions which bring the group closer to the target. What is the role of signalling for the achievement of these goals? Is signalling used by robot R_{AL}

[5] The movies of the performances of the group in both environments are available at `http://iridia.ulb.ac.be/supp/IridiaSupp2006-006/`.

to communicate to robots R_{IR} information concerning the relative position of the target? Similarly, is signalling used by robots R_{IR} to inform robot R_{AL} on the position of obstacles against which it may collide? In order to provide an answer to this type of questions, we carried out a series of tests that look at the properties of the sound signals perceived by each robot during a successful trial in each environment.

In particular, for robots group n. 9, we proceeded by separately recording the "self" and the "non-self" components of the sound perceived by each microphone, and the heading at each time-step of each robot during a successful trial in each environment. Subsequently, with a Fast Fourier Transform analysis (FFT), we looked at these signals in order to identify oscillatory phenomena or other distinctive features in sound production/perception whose properties can be exploited by the robots to coordinate their actions. For the sake of synthesis, we omit the description of the analysis we carried out. The reader can find all the details at `http://iridia.ulb.ac.be/supp/IridiaSupp2006-006/`. In the remaining of this section, we summarise and discuss the results of our tests.

Before proceeding further, we should remind the reader that the intensity of sound perceived by each microphone results from the summation of two components—the "self" and the "non-self"—and the noise. The "self" component (i.e., the agent's own signal) is only determined by the intensity of the sound emitted by the robot itself. The "non-self" component is determined by the intensity at which the sound is emitted from the loud-speaker of a sender as well as by the relative distance and orientation of the loud-speaker with respect to the receiver's microphones (see section 5). Although the agents have no means to distinguish between the "self" and the "non-self" components of the perceived sound, they can act in a way to determine patterns in the flow of sensations which are informative on their spatial relationships.

The results of our analysis show that for each robot there are no oscillatory phenomena in sound production. Oscillations are instead observed in the perceived sound. The results also indicate that the oscillations of the perceived sound are produced by the rotational movement of each robot through the effect that the movement has on the nature of the "non-self" components. Further tests on the sound signals reveal that: (a) the mean value of the "self" components contributes to more than 90% of the perceived sound; (b) the "non-self" components are very "weak", possibly due to the relatively "far" robot-robot distances. However, we notice that, if not attenuated by the shadowing effect, the "non-self" plus the "self" component may be sufficient to saturate the sensors' receptive field of the receiver.

This evidence suggests that during navigation, the readings of the sound sensors of each robot may go through oscillations constrained between an upper and a lower bound. The upper bound is reached when the sum of the "self" and the "non-self" component corresponds to a value equal or bigger than the saturation value of the sound sensors (i.e., 1.0). The lower bound is close to the intensity of the "self" component that is reached when the "non-self" components are strongly attenuated by the shadowing effect. These oscillations are very small since they concern less than 10% of the auditory receptive field, and certainly not very regular since the random noise applied to the sensors reading may disrupt the regularity of the oscillations determined by the contingencies (i.e., rotational movements and robots' relative distances). However, in spite of being small and noisy, these oscillations seem to be the only phenomenon related to the perception of sound that play a significant role in the coordination of action of the group. In fact, given a controller sufficiently sensitive to capture them, they may represent a valuable perceptive cue for the receiver to spatially discriminate sound sources and consequently relative position and orientation of the emitter/s. For example, low intensity of sound corresponds to conditions in which the body of the receiver is placed in between its sound receptor and the sound source; high intensity of sound corresponds to conditions in which the sound receptor is in between the body of the receiver and the sound source. Robots capable of detecting these spatial relationships can use them to make movements towards or away from a sound source. Moreover, the oscillations of perceived sound, produced by the rotational movement might emphasise the intensity differences between the two sound receptors. These differences also known as Interaural Intensity Differences [hereafter referred to as IIDs, see 16] may provide the robots the cues to adjust their positions relative to each other. These cues might be exploited by the robots to remain close to each other while avoiding collisions and moving towards the target. Given the lack of complexity in robots' sound production, we tend to exclude that signalling behaviour concerns more articulated forms of communication.

8.4 Group n. 9: Signalling behaviour and the group's coordination of actions

[Insert here Figure 8]

The results of post-evaluation tests described in the previous section led us to formulate a series of hypotheses concerning the mechanisms the robots may use to cooperate and coordinate their actions. In particular, we identified oscillatory phenomena in sound perception which may represent the structures that underpin the successful navigational strategies described in section 8.2.

In this section, we describe further post-evaluation tests which are meant to gather empirical evidence in support of our hypotheses. This is because the observation of the phenomena described in previous sections is not sufficient to rule out the possibility that sound signalling is partially or totally operationally irrelevant to the achievement of successful navigational strategies. In fact, the use of sound may be limited to robot R_{AL}. Robots R_{IR} may ignore the sound and base their movements on the readings of the infrared sensors. This would be sufficient to keep both robots R_{IR} close to robot R_{AL}. The latter, by moving towards the target, would inevitably bring the group to the light. Another possibility is that none of the robots use sound. In this case, the group might employ "unchanging" phototactic movement which may work as well given that the dimensions of the corridors and the positions of the lights in the two environments do not vary. For example, robot R_{AL} may move for about 65 cm east/west according to the characteristics of the environment and then south; robots R_{IR} have simply to follow R_{AL} avoiding collisions.

The tests we describe in the remain of this section provide us further evidence (a) to strengthen our hypothesis concerning the functional meaning of oscillations in robots' perceived sound, and (b) to rule out the hypothesis that sound is operationally irrelevant. In particular, our goal is to demonstrate that sound is really essential for the robots to coordinate their movements and that the oscillations of perceived sound, produced by the robots' rotational movement is indeed the perceptual phenomenon the agents exploit to mutually coordinate their actions.

We run two post-evaluation tests, *Test A*, and *Test B*. In both tests, we interfere with the propagation of sound in the environment by disrupting the orientation of the robot emitter with respect to the heading of the receiver (see Figure 11). In particular, in each test, the robots undergo sets of 1200 trials in each type of environment. For all the simulation cycles following the first 10 seconds[6] of each trial of a set, the sound sensors reading of a type of robot (i.e., R_{AL} or R_{IR}) are computed with respect to a hypothetical state of the system in which each robot of the other type is supposed to be re-oriented by a fixed angular displacement, ranging from a minimum of $18°$ to a maximum of $180°$, with a randomly chosen direction (clockwise or anti-clockwise) with respect to the heading of the receiver. The magnitude of the angular displacement does not vary in each set of 1200 trials in a given environment. Note that, the updating of the infrared sensors of robots R_{IR} and of the ambient light sensors of R_{AL} do not undergo any disruption during these tests. The hypothetical states are taken into account only for updating the sound sensors' reading of one type of robot at a time. In particular, in *Test A*, the sound perceived by robot R_{AL} is computed with reference to a hypothetical state in which the orientation of both robots R_{IR} with respect to R_{AL}'s heading is changed in order to meet the angular displacement requirements (see Figure 11a). No disruptions are applied to update the sound perceived by robots R_{IR}. In *Test B*, the sound perceived by the robots R_{IR} is computed with reference to a hypothetical state in which the orientation of robot R_{AL} with respect to the R_{IR}'s heading is changed in order to meet the angular displacement requirements (see Figure 11b). In this type of tests no disruptions are applied to update the sound perceived by robot R_{AL}.

From what said above, we can infer that *Test A* and *Test B* disrupt any kind of regularities in the perception of sound which are linked to sender-receiver relative orientation. In particular, by varying the sender-receiver orientation, we indirectly increase/decrease the magnitude of the "non-self" component. In section 8.3, we have seen that oscillations of the perceived sound and IIDs are the only two phenomena of signalling behaviour which might be used by the robots to coordinate their actions. In *Test A* and *Test B*, spatial cues provided by these two phenomena do not refer anymore to the current status of the system

[6] Applying any disruptions after 10 s (i.e., 100 simulation cycles) gives time to the controllers to reach a functional state different from the initial one, arbitrarily chosen by the experimenter, in which the cell potential of the neurons is set to 0 (see section 6).

but to hypothetical states "artificially" introduced. Consequently, a drop in the group performance at *Test A* is a sign that these cues are exploited by the robot R_{AL} to successfully carry out their task. Similarly, a drop in the group performance at *Test B* is a sign that these cues are exploited by the robots R_{IR} to successfully carry out their task. If both type of tests show a drop in the group performance, we would say that sound signalling is a common means of communication exploited by both types of robots to mutually coordinate their actions.

[Insert here Figure 9]

The results of *Test A* are shown in Figure 11a and 11b. The results of *Test B* are shown in Figure 11c and 11d. From these graphs we notice that the performance of the group is significantly disrupted by alterations which concern the orientation of one type of robot with respect to the heading of the other type of robot. In particular, the bigger the magnitude of the angular displacement, the higher the percentage of failure of the system. The majority of failure are due to robot-wall collision. Observing the behaviour of the group in these conditions, we noticed that, under the effects induced by the disruptions, the robots are not capable of remaining close to each other—i.e., within the infrared sensors' range. When the distances becomes too high, the robots start wandering around the arena, and the trial terminates due to a collision of the robot R_{AL} with the arena walls. Only in few circumstances the robots do not lose contact to each other but they are not capable of reaching the target within the time-limits (see Figure 11 black area of the bars).

These results prove that the group performance is severely disrupted when the hypothetical status of the system, used to update the sound sensor readings of either type of robot, is significantly different from the current circumstances. If the oscillations of the sound sensors' reading and IIDs of either type of robots do not reflect the environmental contingencies, the group performance in both environments is disrupted. We conclude that, for both types of robots, spatial cues provided by the oscillations of perceived sound and possibly by IIDs have a bearing on the development of effective navigational strategies. Sound signalling seems to be a common means of communication exploited by both types of robots to mutually coordinate their actions.

8.5 Group n. 9: The significance of the Interaural Intensity Differences (IIDs)

[Insert here Figure 10]

The results of the tests illustrated in the previous section backed up our claim concerning the operational value of sound for the robots' coordination of actions. We now turn our attention to the phenomena of IIDs, to establish whether the latter are cues used by the robots to coordinate their actions. Alternatively, oscillations of perceived sound may be sufficiently informative on the contingencies to allow the robots to successfully accomplish their goal.

In these tests we progressively reduce the IIDs up to the point at which the two sound receptors (S1 and S2) of a type of robot are impinged by the same stimulus. Consequently, these disruptions hinder the possibility of the robots to use IIDs as cues for localisation of sound sources and for their coordination of actions. At the same time, we preserve the phenomenon of oscillations of perceived sound as cues for spatial discrimination and localisation of sound sources.

In each test, the robots undergo sets of 1200 trials in each type of environment. For all the simulation cycles following the first 10 seconds of each trial of a set, the reading of one sound sensor (i.e., S1 or S2) of a type of robot (i.e., R_{AL} or R_{IR}) are modified in order to reduce the IID of a given percentage, ranging from a minimum of 10% to a maximum of 100% (i.e., both sensors return the same reading). The magnitude of the decrease of the IIDs does not vary in each set of 1200 trials in a given environment. Disruptions which reduce the IIDs of a given percentage are independently applied to (i) robot R_{AL} and robots R_{IR}, (ii) sound sensor S1 and S2, and (iii) *Env. L* and *Env. R*, for a total of 8 different types of tests—two types of robots times two types of sound sensor times two types of environment. If we observe a sensible drop of the percentage of success of the group for disruptions applied to any of the two types of robot in any of the two types of environment regardless of the sound sensor disrupted (S1 or S2), then we conclude that, for that type of robot, IIDs are cues used to coordinate its actions during the navigation towards the light. In any other circumstances, we conclude that the oscillations of perceived sound, without IIDs, are sufficiently informative on the contingencies to allow the robot to successfully accomplish their goal.

The results of the full series of tests, available at `http://iridia.ulb.ac.be/supp/IridiaSupp2006-006/`, show that for both types of robots and for both sound sensors, the progressive reduction of the IIDs is associated with a drop in performance of the group. Figure 11 show only the results of tests in which, regardless the sound sensor disrupted, the rate of failure of the group in a type of environment is above 90% when the IIDs are made unavailable to a type of robot (see Figure 11 last bar of each graph). These tests are those in which disruptions are applied to sound sensors S1 and S2 of robot R_{AL} in *Env. L* (see Figure 11a and b) and of robots R_{IR} in *Env. R* (see Figure 11c and d). In these cases, we conclude that, IIDs are cues strictly necessary for a specific type of robot to be able to coordinate its actions.

In all the other cases (robot R_{AL} in *Env. R*, and robots R_{IR} in *Env. L*), although a progressive reduction of the IIDs correspond to a drop in performance of the group, the disruptions applied to any of the two sound sensors do not equally affect the performance of the group. With the IIDs completely removed, the rate of failure of the group range in between 40% and 60% in case in which disruptions concern (i) robot R_{AL} sound sensor S2 in *Env. R*; and (ii) robots R_{IR} in *Env. R* (see graphs at `http://iridia.ulb.ac.be/supp/IridiaSupp2006-006/`). Further analyses of the behaviour of the group under these circumstances are required in order to provide an explanation to these results. These analyses will be carried out in future works. However, we tend to believe that the group might be able to assume spatial configurations which facilitate the navigation in spite of the absence of IIDs for either type of robot.

9 Discussion

The results illustrated in section 8 have shown that dynamical neural networks, shaped by artificial evolution, can be successfully used to design homogeneous control structures for a group of morphologically heterogeneous cooperating and communicating robots. Post-evaluation analyses unveiled the mechanisms which underpin the cooperation and coordination of actions of the group. In particular, we focused on the study of the evolved acoustic communication protocol of the best evolved successful group. First we showed that: (i) all the robots emit sound at a very high intensity; (ii) signalling behaviour is not characterised by oscillatory phenomena; (iii) periodic phenomena, generated by the receiver through a rotational movement associated to the phototaxis, characterise the perception of sound. Then, we proved that oscillations of perceived sound and Interaural Intensity Differences (IIDs) are cues largely exploited by the robots to generate adaptive actions to safely navigate (i.e., without collisions) towards the target. In particular, the robots exploit these cues to regulate their individual actions with respect to the relative position of sound source(s).

It is reasonable to consider that the evolved behavioural and communication strategies illustrated in section 8 are limited to the peculiarities of our simulations. However, our successful results point to the relevance, for the robotics community, of features of our methodological approach which are of more general applicability and re-usable in future research works dealing with the design of homogeneous controllers for groups of heterogeneous cooperating and communicating robots. In particular, we draw the attention of the reader on the following distinctive features of our work: (i) the model of the sound; (ii) the way in which the controllers are wired-up with the sensory apparatus of the robots; (iii) the "dynamic speciation" of the homogeneous controller, whose mechanisms underpin sensory-motor coordination and social interactions in structurally different agents. In the remaining of this section, we further discuss these issues, whose significance, in our opinion, goes beyond the research work illustrated in this paper.

As far as it concerns the model of sound, although inspired by the work of Di Paolo [7], it presents peculiarities of particular interest. As in Di Paolo [7], and contrary to other experimental works in ER, we did not make use of directional microphones, or any other form of hard-wired/hand-coded mechanisms to discriminate between different sound sources or between "self" and "non-self" produced sound. For example, in the work of Marocco and Nolfi [19], four directional microphones capture the sound of the nearest robot located within $\pm 45.0^{\circ}$ left or right of each microphone. As well as hardly portable on a physical system, these types of models preclude the possibility to investigate the principles underlying behavioural coordination through sound signalling in a team of autonomous agents. This follows from the fact that in these models the problem of synchronisation or turn-taking to avoid mutual interference, and of spatial discrimination of sound sources, are eluded thanks to the implementation details. With respect to what described in Di Paolo [7], we strongly simplified the characteristics of the robot's controller. In particular, we did not implement the neural structures which provide the agents in Di Paolo's work the means to further regulate the intensity of emission of sound [i.e., regulation for sound effector, see 7] and the receptiveness of the sound sensory neurons [i.e., sensory gain regulation, see 7]. We simplified the mechanisms to constrain the production of sound by fixing a limit to the intensity of the signal which also correspond to the saturation level of the sound sensors. That is, the "self" produced sound can completely saturate the sound sensors of the emitter. Although arbitrarily implemented by the authors, these simplifications were introduced to compensate for an increase in structural complexity of the controller due to the nature of the agents' sensory apparatus. In particular, while in the work described in [7] the agents are equipped only with sound sensors, in this work the agents are equipped with sound receptors as well as light or infrared sensors. Moreover, we investigated teams of three robots instead of two robots. Possibly due to these differences, the evolved solutions in Di Paolo's work and in ours diverge significantly. While in Di Paolo's 2000 model oscillations and synchronisation in sound production underpin behavioural coordination, in our model, there is no oscillation in sound production.

From an engineering point of view, it is worth to mention that, although extremely effective in terms of collisions, the best evolved navigation strategies are not characterised by a fast phototactic movement. On the one hand, the strong rotational movement allows for behavioural coordination through sound signalling, as explained above. On the other hand, it slows down the movement towards the light. We believe that alternative navigation strategies can potentially be achieved by reintroducing some of the mechanisms originally proposed in [7]. These mechanisms facilitate the evolution of oscillatory behaviour in sound production and the distinction between "self" and "non-self" components, without having to model phenomena such as time varying frequencies, Doppler effect, etc. A group of robots in which each agent is capable of differentiating between "self" and "non-self" and of associating the intensity of the sound perceived in each ear with the distance to the sound source may favour linear over rotational movements. Other hardware specifications, such as the position of the microphones on the robot body might certainly facilitate the evolution of faster phototactic movement. These issues will be the subject of future investigations.

As far as it concerns the way in which the controllers are wired-up with the sensory apparatus of the robots, we would like to provide further justifications for our implementation choices. Our goal was to generate through artificial evolution a controller capable of guiding both types of robots. For this reason, we chose to keep the group homogeneous with respect to the controllers. That is, at time 0 of each trial, each robot is equipped with exactly the same control structure. However, the properties of the controllers allow for a "dynamic speciation": that is, a differentiation of the functionality of each controller. This evidence emerged from the Fast Fourier Transform analysis as described in section 8.3. In particular, we noticed that robot R_{AL} rotates slightly faster than the other two robots. This suggests that the controllers of robot R_{AL} "adjust" to the physical properties of the robot. This "adjustment" or "differentiation" is determined by the attainment, by each controller, of different stable oscillatory dynamics due to the oscillatory pattern experienced through the robot's sensory apparatus. We also wanted to reduce at a minimum the number of parameters which define the search space of the evolutionary algorithm. For this reason, we decided to use neural structures in which the same input neurons in different networks are linked to different type of sensors (see section 6 for details). Our results suggest that implementation details make possible to generate through artificial evolution homogeneous controllers that can efficiently guide morphologically identical as well as morphologically different groups of robots. In our case, the differences in the flow of sensation coming from different sensory channels (i.e., infrared sensors, ambient light and sound sensor) contribute to induce the specialisation of the controllers with respect to the physical characteristics of the robots, and to the relative role that they play in the group (i.e., the "dynamic speciation"). This latter mechanism can also be exploited in case of hardware failure, in which an on-line re-assignment of association between agent's sensors and network's input neurons might provide a robust mechanism to preserve the functionality of multi-robot systems. However, in order to efficiently exploit our methodological choices in the latter context, further investigations are required to determine the plasticity of controllers in those circumstances in which they have already undertaken a process of "dynamic speciation". That is, it is an open question whether a neuro-controller already specialised to receive as input the reading of a particular set of sensors is capable of "redefining" its functionality to guide a robot with a different set of sensors.

10 Conclusions

In a context in which robots differ in their sensory capabilities, cooperation and coordination of actions of the group is achieved by using an acoustic communication protocol controlled by evolved neural mechanisms. Acoustic signals, determined by the individual emission of a single frequency tone, provide the perceptual cues used by the robots to go beyond the limits of their sensory apparatus in order to obtain robust phototactic strategies as well as obstacle avoidance behaviour. The results of a series of post-evaluation tests carried out on the behavioural strategies of the best evolved group of robots, show interesting operational aspects of the system (see sections 8.3, 8.4 and 8.5). In particular, our analyses highlighted fundamental relationships between the motion of the agents and the appearance of waveforms in sound perception [i.e., affordances, see 13] which are exploited by the robots to mutually coordinate their actions. We also provided evidence that the agents' motion is guided by mechanisms that exploit

Interaural Intensity Differences: that is, cues used by natural organisms to localise sound sources.

To conclude, from the results of this research work we learn something about how evolution gets to exploit the physics of our system to develop group navigational strategies based on the mutual coordination of actions and cooperation among the agents. The results of this research work are a "proof-of-concept": they show that dynamic artificial neural networks can be successfully synthesised by artificial evolution to design the neural mechanisms required to underpin the behavioural strategies and adaptive communication capabilities demanded by this task. The analysis of evolved individual and social skills give us an estimation of the potentiality of our implementation choices at various levels, from the model of sound to the characteristics of the robots' controller. Although the evolved behavioural and communication strategies may be limited to the peculiarities of this case study, our methodological approach is of more general applicability. In particular, the "dynamic speciation" of the robots' controllers as well as the elements of the models which bring forth the causal relationships between the physics of the system and the nature of the best evolved collective strategies are contributions of our work that roboticists can employ for the design of more complex forms of social interactions and communication in groups of autonomous robots.

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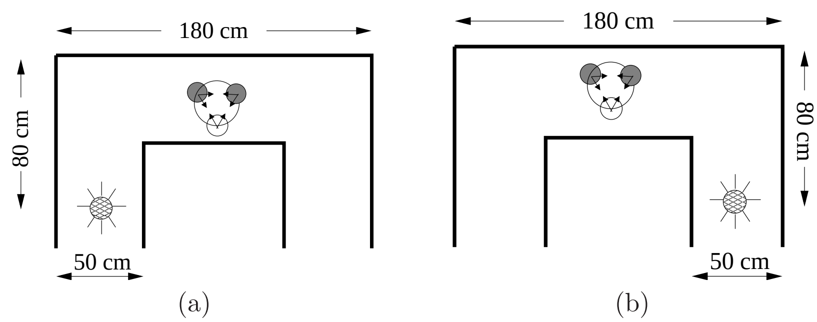


Figure 1: (a) *Env. L*; (b) *Env. R*. In both pictures, the thick lines represent the arena walls; the two small filled circles represent robots R_{IR}, the small white circle represents robot R_{AL}; the light is represented by the filled circles at the bottom left/right. For each robot, the black arrows indicate the region within which the robot's heading is randomly chosen.

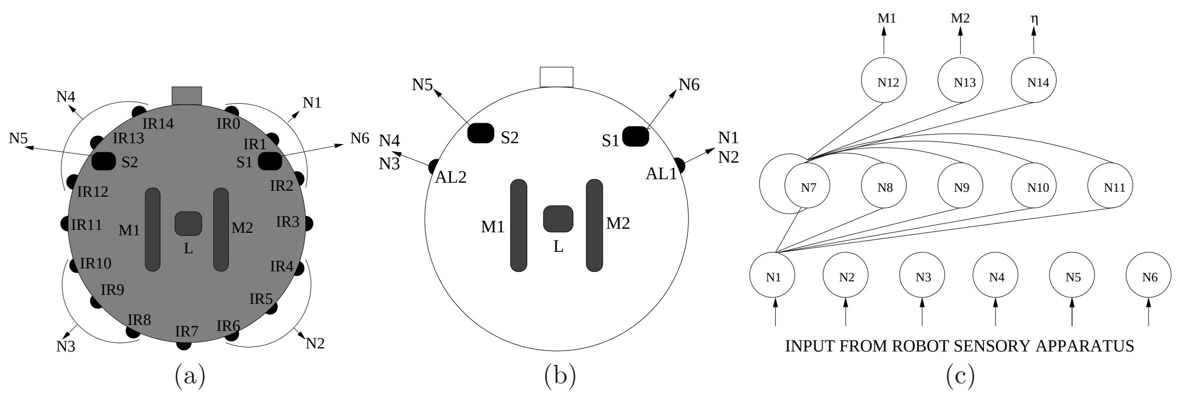


Figure 2: (a) The robots R_{IR}; (b) The robots R_{AL}; (c) the network architecture. Only the connections for one neuron of each layer are drawn. The input layer of R_{IR} takes readings as follows: neuron N_1 takes input from the infrared sensors $\frac{IR_0+IR_1+IR_2}{3}$, N_2 from $\frac{IR_4+IR_5+IR_6}{3}$, N_3 from $\frac{IR_8+IR_9+IR_{10}}{3}$, N_4 from $\frac{IR_{12}+IR_{13}+IR_{14}}{3}$, N_5 from sound sensor S_2, and N_6 from sound sensor S_1. The input layer of R_{AL} takes readings as follows: N_1 and N_2 take input from ambient light sensors AL_1, N_3 and N_4 take input from AL_2, N_5 from S_2, and N_6 from S_1. M_1 and M_2 are respectively the left and right motor. L is the loud-speaker.

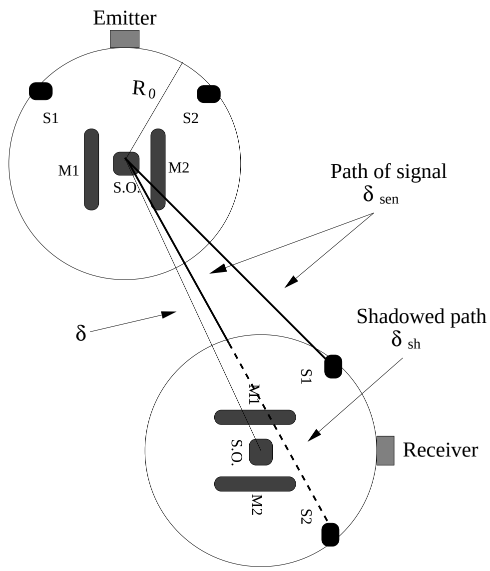


Figure 3: This picture has been adapted from [7]. It shows the working principles of the shadowing mechanism.

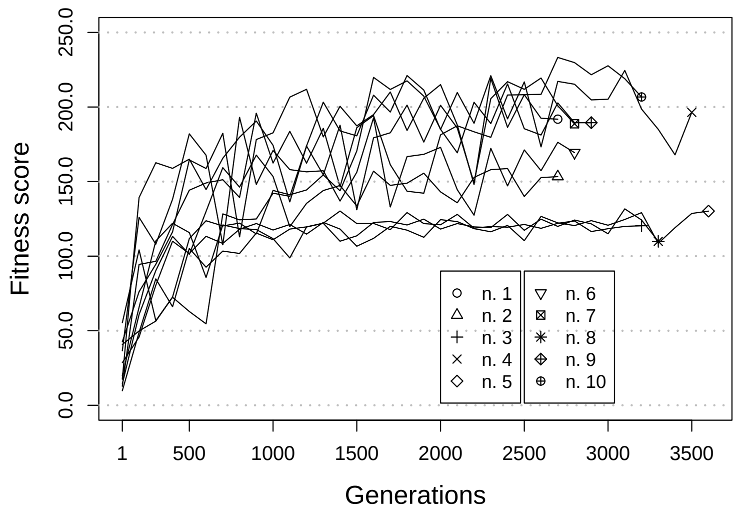


Figure 4: Average Fitness (12 trials) of the best groups at each generation of ten evolutionary runs. The legend indicates the correspondence between evolutionary runs and post-evaluated groups (see section 8.1 for details).

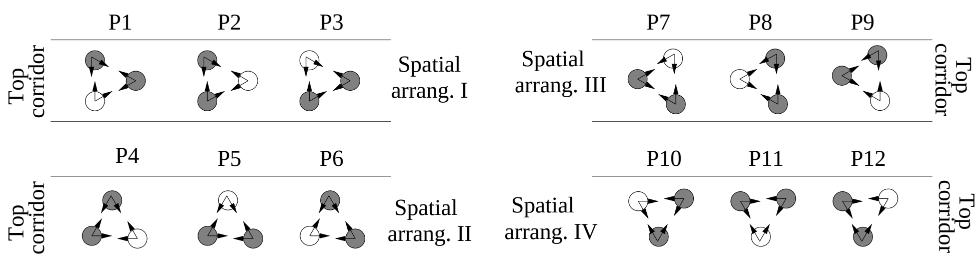


Figure 5: The robots' initial positions (from P1 to P12) during the post-evaluation phase. White circles refer to robot R_{AL}, grey circles refer to robot R_{IR}. For each robot, the black arrows indicate the region within which the robot's heading is randomly chosen. See text in section 8 for details.

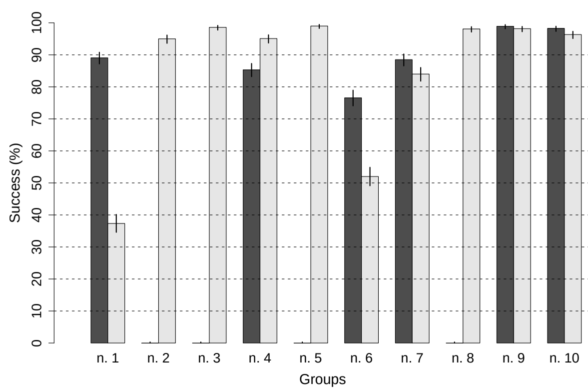
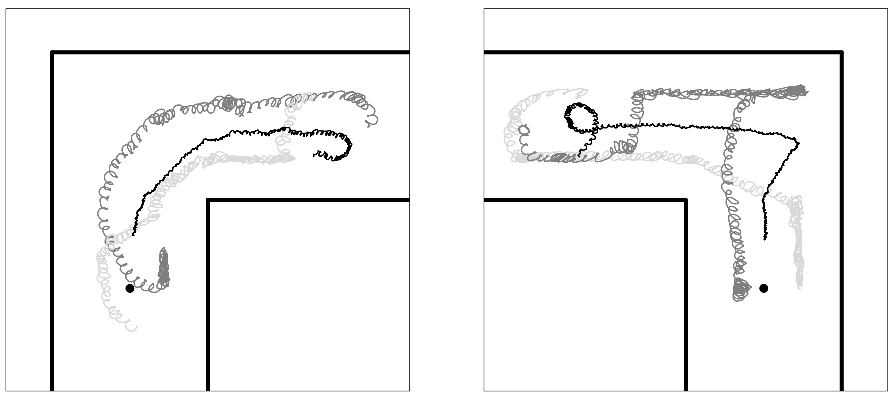


Figure 6: Results of post-evaluation showing the success rate (%) with confidence interval (computed with the binomial test) over 1200 trials per type of environment (black bars refer to *Env. L*, and white bars to *Env. R*) of the groups of robots (n. 1 to n. 10) whose controllers are built from the genotype with the highest fitness of each evolutionary simulation.



(a) (b)

Figure 7: Trajectories of the agents of group n. 9 during a successful trial (a) in an *Env. L*, and (b) in an *Env. R*. The black lines refer to the trajectories of robot R_{AL} while the other lines refer to the trajectories of robots R_{IR}. The thick horizontal and vertical segments represent the walls. In each Figure, we depict only the side of the corridor where the light—i.e., the small black dot—is located.

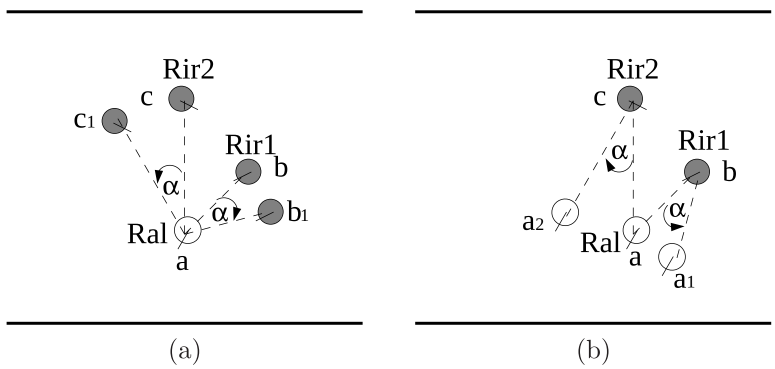
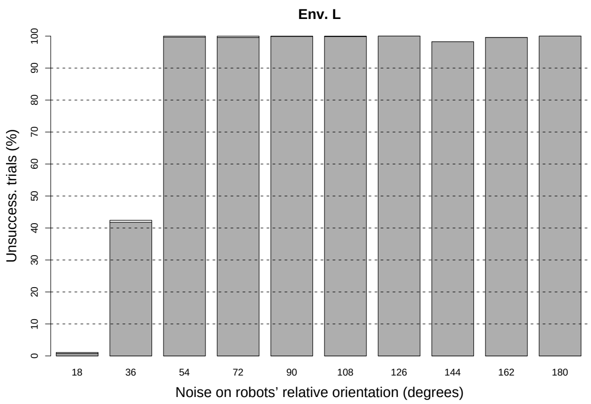
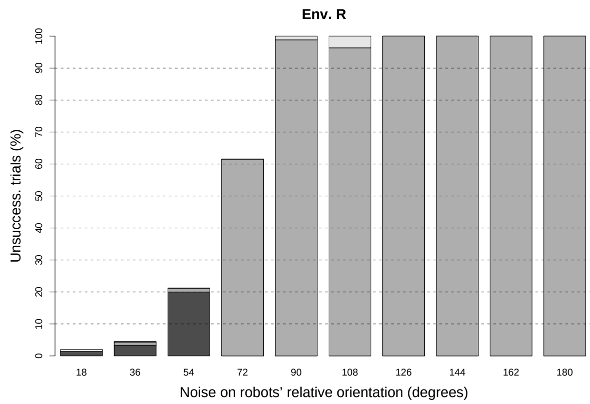


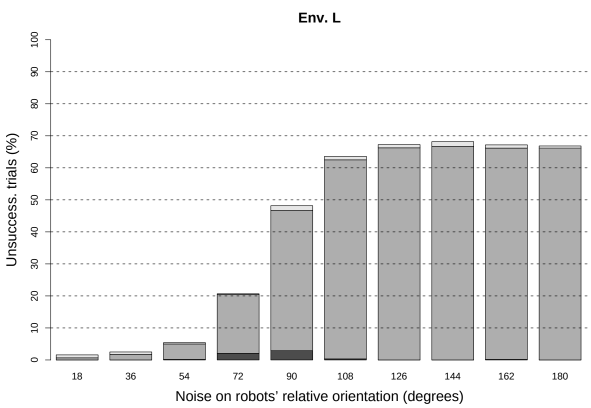
Figure 8: (a) *Test A*: robots R_{IR} (the grey circles) are displaced of an angle α with respect to robot R_{AL} (empty circle). This picture represents a hypothetical state in which the readings of the sound sensors of robot R_{AL} are computed considering R^1_{IR} located in position b_1 instead of b, and R^2_{IR} located in position c_1 instead of c. (b) *Test B*: robot R_{AL} is displaced of an angle α with respect to robots R_{IR}. This picture represents a hypothetical state in which the readings of the sound sensors of robot R^1_{IR} are computed considering R_{AL} located in position a_1 instead of a. The sound sensors of robot R^2_{IR} are computed considering R_{AL} located in position a_2 instead of a.



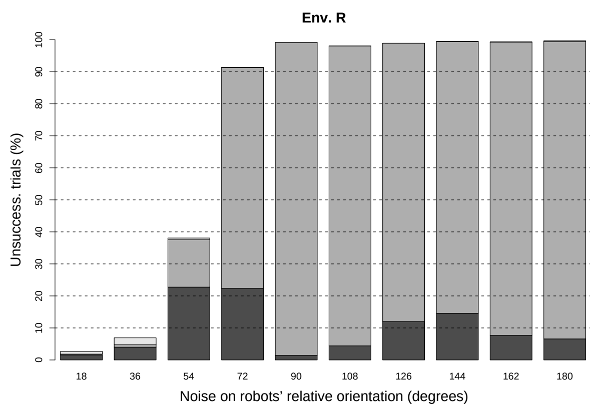
(a)



(b)



(c)



(d)

Figure 9: Percentage of failure during 1200 trials in each type of environment in post-evaluation tests with disruptions applied to the relative orientation of the robots during the computation of the perceived sound. (a) and (b) refer to *Test A*. The robots R_{IR}, during all the simulation cycles following the first 10 seconds of any trial, are considered to be re-oriented with respect to the heading of robot R_{AL} by applying the angular displacement indicated on the horizontal axis and randomly choosing the direction of displacement (i.e., clockwise or anti-clockwise). (c) and (d) refer to *Test B*. The robot R_{AL} is re-oriented with respect to the heading of each robot R_{IR} as explained above. (a) and (c) refer to tests in *Env. L*; (b) and (d) refer to tests in *Env. R*. The black area of the bars refers to the percentage of trials terminated without collisions and with the group not having reached the target. The light grey area of the bars refers to the percentage of trials terminated due to robot-robot collisions. The dark grey area of the bars refers to the percentage of trials terminated due to robot-wall collisions.

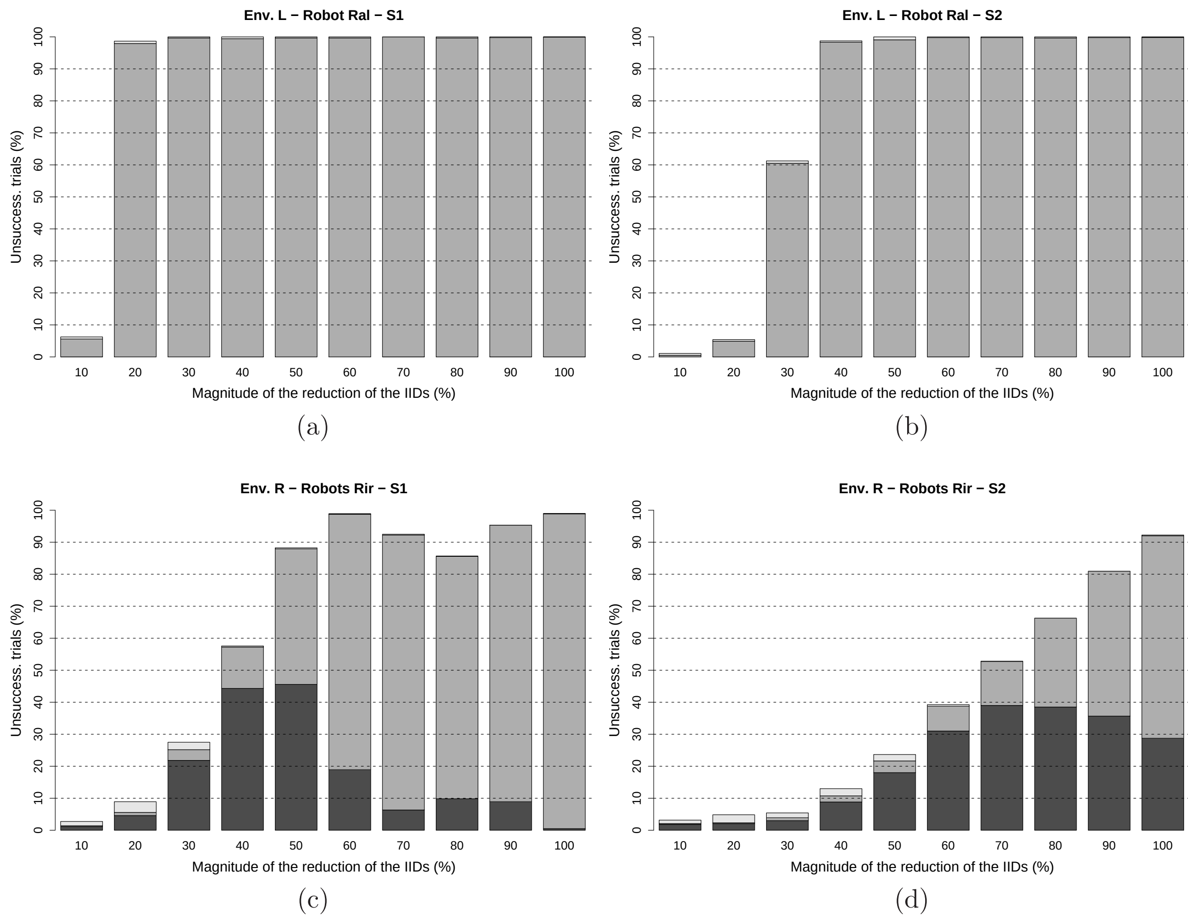


Figure 10: (a) and (b) show the percentage of failure during 1200 trials with disruptions applied to robot R_{AL} sound sensor S1 in *Env. L*, and sound sensor S2 in *Env. R*. (c) and (d) show the percentage of failure during 1200 trials with disruptions applied to robots R_{IR} sound sensor S1 and sound sensor S2 in *Env. L*. The disruptions concern the decrease of the the IIDs of the percentage indicated on the horizontal axis. The black area of the bars refers to the percentage of trials terminated without collisions and with the group not having reached the target. The light grey area of the bars refers to the percentage of trials terminated due to robot-robot collisions. The dark grey area of the bars refers to the percentage of trials terminated due to robot-wall collisions.

Table 1: Further results of the post-evaluation test, showing for the best evolved groups: (i) the percentage of unsuccessful trials due to exceeded time limit without the group having reached the target (columns 2, and 3); (ii) the percentage of unsuccessful trials which terminated due to collisions (columns 4, and 5); (iii) the average and standard deviation of the final distance of the centroid of the group to the light during the unsuccessful trials (respectively columns 6, 8 for *Env. L*, and columns 7, 9 for *Env. R*). Note that in all trials the initial distance between the centroid of the group and the light is equal to 85.14 cm.

	(%) of failure due to time limit		**(%) of failure due to collisions**		**Distance to the light**			
					avg		**std**	
group	***Env. L***	***Env. R***	***Env. L***	***Env. R***	***Env. L***	***Env. R***	***Env. L***	***Env. R***
n. 1	0.00	52.75	10.92	9.92	82.19	52.17	6.63	32.74
n. 2	85.33	1.83	14.67	3.17	66.30	46.17	4.36	18.22
n. 3	0.00	1.00	100.00	0.42	81.02	36.38	4.049	12.02
n. 4	0.67	0.50	14.00	4.50	57.83	69.30	13.50	15.32
n. 5	0.00	0.00	100.00	1.00	79.05	41.13	2.94	12.93
n. 6	0.00	31.00	23.42	17.08	77.50	64.27	11.89	29.92
n. 7	0.58	10.00	10.92	6.00	50.98	40.80	30.18	14.18
n. 8	0.00	0.00	100.00	1.92	80.94	53.03	2.34	11.59
n. 9	0.00	0.83	1.08	1.00	77.71	50.22	11.44	21.08
n. 10	0.00	2.17	1.75	1.50	82.28	90.37	13.19	31.81